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Adaptive Target Tracking in Wireless Sensor Networks Using Metaheuristic-Enhanced Mobility Prediction Scheme

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Abstract: *Wireless Sensor Networks (WSNs) have emerged as critical enablers in a wide array of real-world applications, including surveillance, battlefield monitoring, wildlife tracking, and intelligent transportation. However, mobile target tracking is a complex problem that demands real-time precision, energy efficiency, and adaptability to dynamic network conditions. The limited computational and energy resources of WSN nodes, coupled with the inherent uncertainty in target motion, introduce significant challenges in achieving reliable and long-term tracking. This research presents a multiphase, optimization-driven target tracking framework that addresses these challenges by integrating advanced Kalman filtering techniques with novel metaheuristic algorithms. The research progresses across three well-defined phases: basic prediction-based tracking, distributed adaptive optimization, and robust node-aware tracking.*

In the proposed research, a two-stage tracking scheme was introduced to improve the accuracy and efficiency of tracking mobile targets. The initial stage employed the Adaptive Extended Kalman Filter (AEKF), a widely used estimator capable of handling non-linear system dynamics, to track the target's current position based on sensor data such as Received Signal Strength (RSS) and Angle of Arrival (AoA). Recognizing that mere state estimation is insufficient for anticipating future movements under variable conditions, the second stage introduced a predictive component. To this end, a novel hybrid optimization algorithm named Lion Mutated– Cuckoo Search (LM-CS) was proposed. LM-CS combined the local exploitation ability of the Lion Algorithm with the global search characteristics of the Cuckoo Search Algorithm, thereby enhancing convergence, precision in the prediction of mobile node movement. Performance evaluations demonstrated that the proposed LM-CS-EKF model outperformed traditional approaches like the Elephant Herding Optimizer (EHO) and Particle Swarm Optimization (PSO), achieving lower Mean Absolute Error (MAE) and Mean Squared Error (MSE) under various noise conditions...

Keywords*:* *Wireless Sensor Networks*

I. INTRODUCTION

Wireless Sensor Networks (WSNs) have become a foundational component of modern intelligent systems, enabling a wide array of applications such as environmental monitoring, military surveillance, industrial automation, and mobile target tracking. These networks consist of spatially distributed sensor nodes capable of sensing, processing, and wirelessly communicating data. One of the most critical and challenging applications of WSNs is mobile target tracking, where the objective is to accurately and efficiently determine the trajectory of a moving object within a sensor deployed region. Mobile target tracking in WSNs is inherently complex due to issues such as unpredictable target motion, limited energy resources, dynamic topology, and noisy measurements. Traditional localization techniques like GPS are often impractical due to high energy costs, signal availability constraints, and hardware limitations.

Therefore, the focus has shifted towards using sensor-based localization techniques such as Angle of Arrival (AoA) and Received Signal Strength (RSS), which offer a more practical and energy-efficient alternative. However, these

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techniques are sensitive to noise, interference, and environmental conditions, leading to inaccuracies in target localization and tracking. To address the inherent uncertainty in sensor measurements and mobility, various filtering and prediction models have been proposed. Among them, Kalman Filters (KF) and their variants, particularly the Adaptive Extended Kalman Filter (AEKF), have gained widespread use due to their recursive nature and capability to handle nonlinear systems. Nonetheless, traditional EKF approaches suffer from issues related to convergence and linearization errors when applied in highly dynamic or nonlinear environments.

In addition to filtering, target movement prediction plays a pivotal role in enhancing tracking performance by estimating future target locations, which aids in proactive sensor management and energy optimization. This prediction task is naturally formulated as an optimization problem, especially under dynamic and uncertain conditions. Metaheuristic algorithms have proven to be effective tools for solving such problems due to their ability to escape local optima and handle complex search spaces. Algorithms like Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Cuckoo Search (CS) have shown promise in this domain.

To overcome the challenges of localization inaccuracy, energy inefficiency, and poor prediction under mobility, this research proposes a novel hybrid energy-efficient mobile target tracking framework for WSNs. The system is structured into two core phases:

1. Mobility Target Tracking using Adaptive Extended Kalman Filtering (AEKF): This phase enhances the classical EKF by introducing adaptive parameters that dynamically adjust based on noise characteristics and system behavior, thereby improving tracking robustness and accuracy in nonlinear environments.
2. Target Movement Prediction using a hybrid Lion Mutated–Cuckoo Search (LM-CS) algorithm: This phase focuses on forecasting the future position of the mobile target. The proposed LM-CS algorithm combines the local exploitation strength of the Lion Algorithm (LA) with the global search capabilities of the Cuckoo Search (CS) algorithm. The hybridization ensures a balanced search process that avoids premature convergence while achieving high accuracy in movement prediction.

The integration of AoA and RSS as tracking inputs further enriches the system's situational awareness and localization precision. Through rigorous simulations and benchmarking against existing techniques, the proposed framework demonstrates superior performance in terms of localization accuracy, energy conservation, and convergence rate, making it a significant contribution to the field of mobile target tracking in WSNs.

II. RELATED WORK

Many studies have been conducted in this area. Some highlighted works are represented in this section

In 2016, Singh et al. [1] proposed a localization method for target nodes using a single mobile anchor node, which follows a Hilbert trajectory. The approach utilized conventional PSO and H-Best PSO (HPSO) under a Computational Intelligence (CI)- based framework. This model was designed for distributed, isotropic, range-based, and non-collaborative WSNs. A virtual anchor node projection was introduced to address Line-of-Sight (LoS) challenges, enhancing localization accuracy with minimal infrastructure.

In 2016, Sun et al. [2] introduced a two-layer compressive sensing-based target dynamic localization (TDL) approach, comprising Spatial Localization Module (SLM) and Temporal Localization Module (TLM). SLM utilized RSS sparsity across space, while TLM exploited temporal domain characteristics for improved localization accuracy. Two effective measurement matrices were also proposed, and simulations confirmed the model's superiority in mobile target tracking.

In 2019, Kouroshnezhad et al. [3] has proposed a new mobile anchor trajectory planning model named OPTEC. The MILP optimization technique has been used in the implemented structure to plan the optimal route for deployed sensors using the availability of location uncertainty. Various essential computation metrics were explained for comparing the static mobile anchor trajectory plans. Further, this paper has deployed the static sensors.

In 2019, Sun et al. [4] presented the PP-MMAN model to optimize anchor node path length and energy consumption. To address the boundary node localization issue, a Compensation Algorithm for Positioning (CAP) method was introduced. Comparative analysis validated that PP-MMAN significantly enhanced location efficiency with minimal energy expenditure.

In 2018, Kuo et al. [5] developed an adaptive trap coverage approach using mobile sensors in MSNs and IoT applications. Their model effectively minimized sensor unavailability and reduced target-missing time, improving trap coverage reliability through dynamic sensor movement.

In 2019, Wang et al. [6] proposed an improved Bayesian-based weighted least squares algorithm for WSN-based target localization. This method used predicted subrange probabilities to generate a joint range matrix, followed by normalized weighted computations to estimate target positions. The approach achieved low computational complexity and high localization accuracy.

In 2018, Lersteau et al. [7] addressed sensor energy balancing for WSN-based target tracking by introducing a two-step method: mathematical modeling followed by a hybrid optimization strategy combining column generation and GRASP metaheuristics. The method improved sensor utilization and extended network lifetime during tracking missions.

In 2019, Amir [8] proposed an energy-efficient target tracking method combining prediction and MAC-layer coordination. Sensor nodes dynamically transitioned among monitoring, detection, and sleep states to conserve energy. Only the necessary nodes remained active during tracking, resulting in significant energy savings while maintaining tracking accuracy.

In 2016, Liang et al. [9] introduced a multi-modal WSN architecture integrating camera, RF, and PIR sensors for 3D target tracking. The control layer managed dynamic distances, and the system's optimization was carried out using the Pittsburgh genetic algorithm, which significantly reduced tracking errors through Simulation.

Jondhale et al. [10], [11] made significant contributions from 2020 to 2022. In 2022, they proposed the Centroid-GRNN (C-GRNN) model for improved localization, reducing RMSE and average error. In 2021, they extended this by integrating trilateration with GRNN for better multi-target indoor tracking using RSSI.

In 2020, they explored various training strategies in Feed Forward Neural Networks (FFNN) for localization, aiming to enhance the adaptability and accuracy of neural models in WSNs. In 2023, Madhavi et al. [12] introduced an energy-efficient target tracking model by integrating Particle Filter (PF) with Support Vector Machine (SVM), showing significant improvements in localization and tracking accuracy.

Zhu et al. [13] proposed a Recursive Robust Set-Membership Fusion Estimator (RSMFE) that effectively handled location uncertainty with Unknown But Bounded (UBB) noise and reduced complexity using a novel decoupling strategy.

Zhou et al. [14] developed a hierarchical tracking model leveraging Edge Intelligence (EI) for optimal resource allocation and accurate mobile target tracking.

Zhu et al. [15] further proposed an adaptive event-triggered RSS-based tracking model that ensured accurate localization with low complexity in resource constrained WSN environments.

In 2024, Khiadani and Hendessi [16] designed a two-phase energy-aware Kalman filter-based tracking protocol that dynamically assigns leader nodes for efficient tracking.

Zhu et al. [17] introduced the EAERCKF model, combining robust square root cubature Kalman filtering with adaptive event-driven scheduling for better tracking accuracy.

Khedr et al. [18] presented the EARC-ODCL model, integrating deep convolutional learning and the PRMGOA optimization strategy to improve clustering and reduce data loss.

Siva and Merline [19] proposed the ERBS-REE model utilizing ensemble learning and electric eel-based optimization for high-precision tracking. These models signify a fusion of statistical estimation and adaptive AI, achieving energy-aware precision.

III. RESEARCH METHODOLOGY

A hybrid optimization algorithm combining Lion Optimization and Cuckoo Search is proposed to efficiently estimate targets with improved accuracy and convergence.

3.1 Lion Algorithm (LA)

The Lion Algorithm (LA) [126], inspired by the social behavior of lions, is a metaheuristic optimization technique that simulates lion pride dynamics to evolve optimal solutions. The main stages include: Pride Generation, Fertility

Evaluation, Territorial Takeover, Mating, Territorial Defence, and Termination. The algorithm uses a population of solution vectors referred to as lions and models their behaviour to search the solution space efficiently. This section describes the Lion Optimization–based framework used for continuous optimization. The solution vector is defined within bounded search space limits, and the objective is to minimize a possibly multimodal fitness function. The algorithm initializes a pride consisting of territorial male, territorial female, and nomadic lions, each represented as candidate solutions. Lion length corresponds to solution dimensionality. Nomadic lions participate in territorial defense and solution diversification. Fertility evaluation prevents premature convergence using laggardness, sterility, and update mechanisms. Mating involves crossover and mutation to generate offspring. Nomadic coalition and territorial takeover operators update dominant solutions. The algorithm terminates when fitness convergence or maximum generation count is achieved.

The algorithm is governed by the following idealized rules:

Each lion represents a candidate solution, initialized randomly within bounds and evaluated using a fitness function.

The pride structure includes territorial male, territorial female, and nomadic lions, balancing exploitation and exploration.

Territorial defense, dominance, and elitism ensure survival and preservation of the best solutions.

Fertility, sterility, laggardness, and mating (crossover and mutation) mechanisms generate new solutions and avoid premature convergence.

The algorithm iteratively updates pride composition through territorial takeover and terminates upon convergence or reaching the maximum iterations.

3.2 Cuckoo Search (CS) Algorithm

The Cuckoo Search (CS) [127] algorithm is a nature-inspired metaheuristic optimization technique developed based on the brood parasitism behavior of cuckoo birds. In nature, certain species of cuckoos lay their fertilized eggs in the nests of other birds, expecting that these host birds will incubate and raise their offspring. Occasionally, the host birds identify these foreign eggs and either abandon the entire nest or eliminate the alien eggs.

This reproductive strategy is effectively translated into a computational model, where each solution is represented as a cuckoo egg, and each nest corresponds to a candidate solution in the search space. The algorithm is governed by the following three idealized rules:

1. Each cuckoo lays one egg at a time and places it in a randomly chosen nest.
2. The best nests with high-quality eggs (i.e., best solutions) are carried forward to the next generation.
3. The number of host nests is fixed. A fraction of the worst nests are identified and replaced by new random nests, mimicking the rejection of foreign eggs or nest abandonment by host birds.

During each iteration, the CS algorithm evaluates the quality (fitness) of solutions. A newly generated solution (egg) is used to potentially replace a poorer solution in one of the nests, thus improving the overall solution quality. In this algorithm, there's no need to explicitly differentiate between eggs, nests, or cuckoos -each represents a possible solution vector.

3.3 Proposed Lion Mutated Cuckoo Search Algorithm

The LM-CS algorithm integrates the global exploration capacity of the Cuckoo Search, driven by Lévy flight dynamics, with the local exploitation efficiency of the Lion Algorithm, which models social cooperation and competitive territorial defence. This hybridization allows LM-CS to maintain a dynamic balance between diversification and intensification, thereby reducing the risk of premature convergence and improving robustness in noisy and nonlinear target-tracking environments [126], [127].

The key innovation lies in how solutions are updated. Instead of relying on a single strategy, the update mechanism dynamically switches among CS-based Lévy flight updates, LA-inspired female lion updates, and random mutations depending on the index or status of the current solution in the population.

Rule-Based Update Strategy for the Hybrid Algorithm

Let the population size be fixed at a constant n = 10. For each solution (host nest) in the population, the update rule is determined by the index as follows:

Case 1: $i = 1, 2, 3$

The Cuckoo Search (CS) update rule based on Lévy flight is applied to enhance global exploration:

$$L_i^{t+1} = L_i^t + \alpha \, \text{Levy}(q, \lambda)$$

Case 2: $4 \leq i \leq 6$

The female lion update rule from the Lion Algorithm (LA) is employed to improve local exploitation:

$$M_{\text{new}}^{\text{female}} = M_{\text{old}}^{\text{female}} + \beta\left(M^{\text{male}} - M_{\text{old}}^{\text{female}}\right) + \delta$$

Case 3: $i = 7, 8$

A mutation operator is applied to the current solution to introduce diversity and prevent premature convergence.

Case 4: Otherwise

The solution is updated randomly within the predefined bounds to maintain diversity across the search space.

Algorithm 1 represents the pseudo code of the proposed LM-CS algorithm

Algorithm 1: Hybrid LM-CS Optimization Algorithm

```
Initialize a population of N candidate solutions (nests) randomly
Evaluate fitness of each solution
Rank solutions and identify the current best solution X*
Set generation counter t ← 0
 while t < Gmax do
    t ← t + 1

Lion Mechanism (LM) Phase
    Select elite solutions as lions
    Perform hunting, roaming, and mating operations
    Update population based on LM rules
    Evaluate fitness of updated solutions
Cuckoo Search (CS) Phase
    Generate new solutions using Lévy flights
    Replace a fraction Pa of worst solutions with new nests
    Evaluate fitness of new solutions

    Update and retain the best solution X

end while

 return X
```

IV. RESULT ANALYSIS

The proposed model was implemented in MATLAB, and its performance was evaluated against several conventional optimization algorithms, including Lion Algorithm (LA) [20], Cuckoo Search (CS) [21], Elephant Herding Optimization (EHO) [22], Particle Swarm Optimization (PSO) [23], and Salp Swarm Algorithm (SSA) [24]. The evaluation was carried out using various error metrics and analyzed under different configurations.

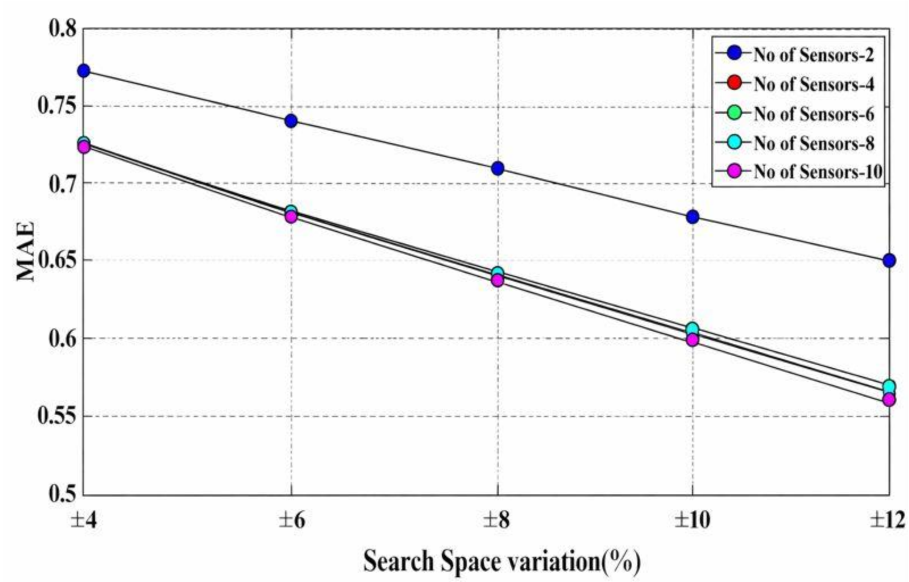

Figure 1: MAE Analysis with varying search space and sensor count

Figures 1 and 2 demonstrate that increasing both the search space (±4% to ±12%) and the number of static sensors significantly improves tracking accuracy. As the search space widens, MAE consistently decreases across all sensor configurations, with more pronounced reductions observed when a higher number of sensors is deployed.

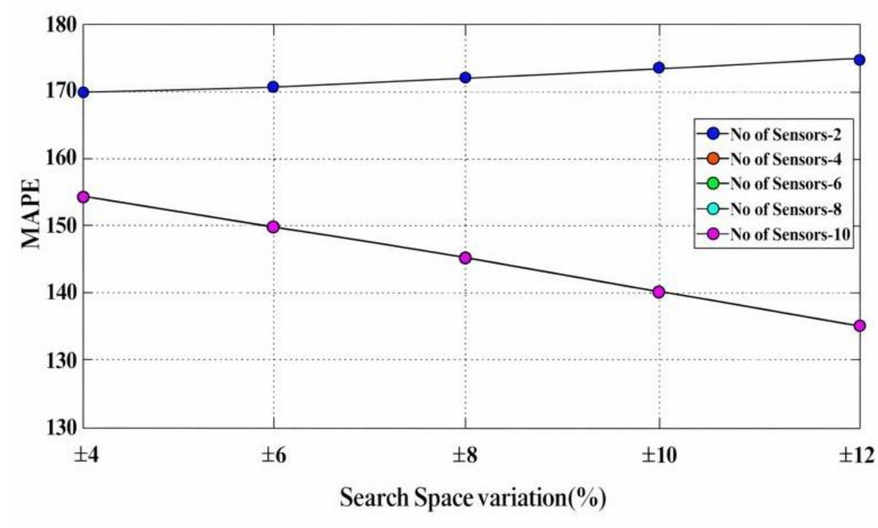

Figure 2: MAPE Analysis with varying search space and sensor count

Similarly, MAPE shows a steady decline with increasing sensor density, indicating enhanced estimation reliability. Configurations with fewer sensors exhibit higher error levels, whereas deploying up to 10 sensors yields substantial improvements, particularly at larger search spaces. Overall, these results confirm that a wider search space combined with higher sensor density enhances localization precision, robustness, and scalability of the proposed WSN tracking framework.

Figure 2 shows that MSE consistently decreases as both the search space (±4% to ±12%) and the number of static sensors increase. Lower sensor configurations exhibit higher errors, while deploying more sensors leads to a sharper reduction in MSE, particularly at wider search spaces. With higher sensor densities, MSE converges to low values,

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indicating improved estimation accuracy and reduced sensitivity to further sensor increases. These results validate that an appropriately chosen search space and sufficient sensor deployment enhance the robustness and accuracy of the proposed tracking model in WSN environments.

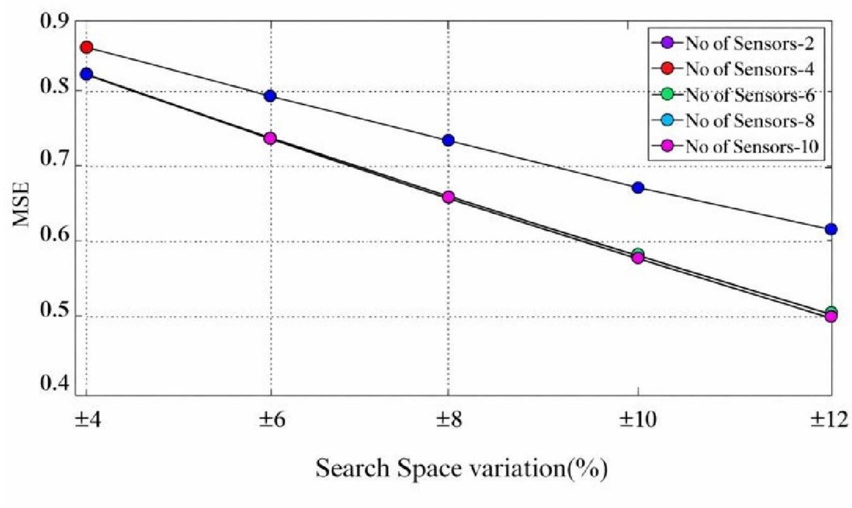

Figure 3: MSE Analysis with varying search space and sensor count

Figure 3 illustrates that RMSE decreases steadily with increasing search space (±4% to ±12%) and higher sensor density. Configurations with fewer sensors exhibit larger errors, while deploying more sensors leads to significant RMSE reduction, particularly at wider search spaces. The convergence of RMSE values for higher sensor counts indicates stable and reliable estimation performance. Overall, the results confirm that optimized search space selection and sufficient sensor deployment effectively enhance the precision and robustness of the proposed target tracking model in WSN environments.

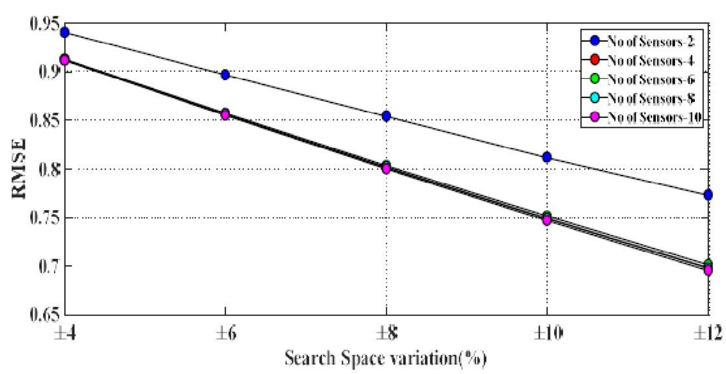

Figure 4: RMSE Analysis with varying search space and sensor count

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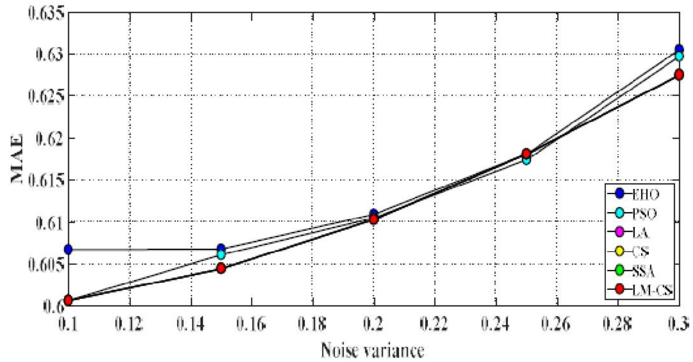

Figure 5: MAE Comparison under varying noise variance for different optimization algorithms

Figure 5 shows that MAE increases with higher noise variance for all algorithms, reflecting the adverse effect of noise on tracking accuracy. However, the proposed LM-CS consistently achieves the lowest MAE across all noise levels, with only a marginal increase from 0.600 to 0.627 as variance rises from 0.1 to 0.3. Compared to EHO, PSO, LA, CS, and SSA, LM-CS demonstrates superior robustness and noise tolerance, confirming its effectiveness and reliability for target tracking in noisy WSN environments.

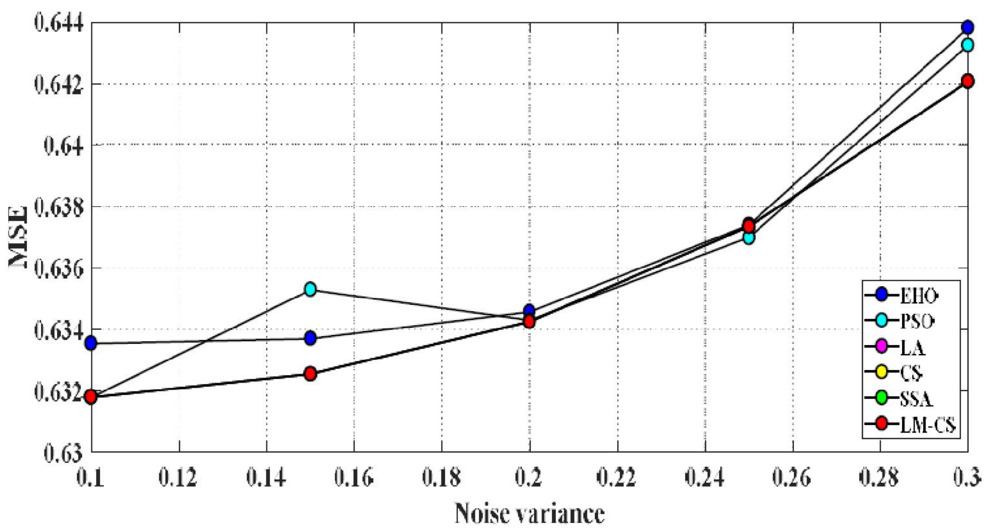

Figure 6: MSE Comparison under varying noise variance for different optimization algorithms

Figure 6 indicates that MSE increases with rising noise variance for all algorithms, reflecting reduced estimation accuracy under noisy conditions. However, the proposed LM-CS consistently records the lowest MSE across all noise levels, showing only a minimal increase from 0.631 to 0.643 as variance rises from 0.1 to 0.3. Compared to EHO, PSO, LA, CS, and SSA, LM-CS demonstrates superior robustness and noise resilience, confirming its effectiveness for accurate target tracking in noisy WSN environments.

V. CONCLUSION

This paper presented a centralized LM-CS-AEKF hybrid framework for WSN target tracking, achieving significant improvements in accuracy, robustness, and convergence speed. By optimally tuning Kalman gain parameters through a balanced exploration–exploitation strategy, the model reduced MAE by 29.68% and consistently outperformed conventional metaheuristic and standalone filtering methods across varying noise levels. Stable convergence under high noise variance and effective fusion of RSS and AoA measurements further enhanced prediction stability, scalability, and localization accuracy. Overall, the proposed LM-CS-AEKF framework demonstrates strong potential for robust and precise target tracking in noisy WSN environments.

REFERENCES

[1]. Singh, P., Khosla, A., Kumar, A., & Khosla, M. (2018), "Optimized localization of target nodes using single mobile anchor node in wireless sensor network", "*AEU – International Journal of Electronics and Communications"*, Vol. 91, PP: 55–65, ISSN (print): 1434-8411; E-ISSN: 1618-0399

[2]. Sun, B., Guo, Y., Li, N., Peng, L., & Fang, D. (2016), "TDL: Two-dimensional localization for mobile targets using compressive sensing in wireless sensor networks", "*Computer Communications"*, Vol. 78, PP: 45–55. ISSN: 0140-3664

[3]. Kouroshnezhad, S., Peiravi, A., Haghighi, M. S., & Zhang, Q. (2019), "A mixed-integer linear programming approach for energy-constrained mobile anchor path planning in wireless sensor networks localization", "*Ad Hoc Networks"*, Vol. 87, PP: 188–199, ISSN: 1570-8705

[4]. Sun, S., Zhao, J., Tian, X., & Zhang, J. (2019), "Path planning for multiple mobile anchor nodes assisted localization in wireless sensor networks", "*Measurement"*, Vol. 141, PP: 124–136, ISSN: 0263-2241.

[5]. Kuo, C.-H., Chen, T.-S., & Syu, S.-C. (2018), "Robust mechanism of trap coverage and target tracking in mobile sensor networks", "*IEEE Internet of Things Journal"*, Vol. 5, Issue 4, PP: 3019–3030, ISSN: 2327-4662.

[6]. Wang, T., Wang, X., Shi, W., Zhao, Z., He, Z., & Xia, T. (2020), "Target localization and tracking based on improved Bayesian enhanced least-squares algorithm in wireless sensor networks", "*Computer Networks"*, Vol. 167, 106968, ISSN: 1389-1286.

[7]. Lersteau, C., Rossi, A., & Sevaux, M. (2018), "Minimum energy target tracking with coverage guarantee in wireless sensor networks", "*European Journal of Operational Research"*, Vol. 265, Issue 3, PP: 882-894, ISSN: 0377-2217.

[8]. Javadpour, A. (2019), "An Optimize-Aware Target Tracking Method Combining MAC Layer and Active Nodes in Wireless Sensor Networks", "*Wireless Personal Communications"*, Vol. 108, PP: 711–728, ISSN: 0929-6212.

[9]. Yu, X., & Liang, J. (2018), "Genetic Fuzzy Tree Based Node Moving Strategy of Target Tracking in Multimodal Wireless Sensor Network", "*IEEE Access"*, Vol. 6, PP:25764-25772, ISSN: 2169-3536.

[10]. Jondhale, S. R., Wakchaure, M. A., Agarkar, B. S., et al. (2022), "Improved generalized regression neural network for target localization", "*Wireless Personal Communications"*, Vol. 125, PP: 1677–1693, ISSN: 0929-6212.

[11]. Jondhale, S. R., Jondhale, A. S., Deshpande, P. S., Lloret, J. (2021), "Improved trilateration for indoor localization: Neural network and centroid-based approach", "*International Journal of Distributed Sensor Networks"*, Vol. 17, Issue 11, ISSN: 1550-1329.

[12]. Madhavi, K. R., Nawi, M. N. M., Reddy, B. B., Baboji, K., Kishore, K. H., Manikanthan, S. V. (2023), "Energy efficient target tracking in wireless sensor network using PF-SVM (particle filter-support vector machine) technique", "*Measurement: Sensors"*, Vol. 26, PP:1-5, 100667, ISSN: 2665-9174.

[13]. Zhu, H., Luo, J., Luo, M., Minane, J. (2023), "A Recursive Robust Set- Membership Estimator for WSN-Assisted Moving Targets Tracking With UBB Anchor Location Uncertainty", "*IEEE Transactions on Vehicular Technology"*, Vol. 72, Issue 5, PP: 6547-6557, ISSN: 0018-9545.

[14]. Zhou, L., Leng, S., Liu, Q., Chai, H., Zhou, J. (2022), "Intelligent Sensing Scheduling for Mobile Target Tracking Wireless Sensor Networks", "*IEEE Internet of Things Journal"*, Vol. 9, Issue 16, PP: 15066-15076, ISSN: 2327-4662.

[15]. Zhu, H., Chen, H., Luo, M. (2022), "Adaptive Event-Driven Robust Set-Membership Estimation for Received-Signal-Strength-Based Moving Targets Localization", "*IEEE Internet of Things Journal"*, Vol. 9, Issue 14, PP: 12825-12835, ISSN: 2327-4662.

[16]. Khiadani, N., Hendessi, F. (2025), "An energy efficient prediction based protocol for target tracking in wireless sensor networks", "*Ad Hoc Networks"*, Vol. 167, 103688,ISSN: 1570-8705.

[17]. Zhu, H., Wu, H., Luo, M. (2023), "Environmentally adaptive event-driven robust cubature Kalman filter for RSS-based targets tracking in mobile wireless sensor network", "*IEEE Internet of Things Journal"*, Vol. 10, Issue 6, PP: 5530–5542, ISSN: 2327-4662.

[18]. Khedr, A. M., Rani, S. S., Saad, M. (2023), "Optimized deep learning for congestion-aware continuous target tracking and boundary detection in IoT assisted WSN", "*IEEE Sensors Journal"*, Vol. 23, Issue 7, PP: 7938–7948, ISSN: 1530-437X.

[19]. Siva, T., Merline, A. (2024), "Optimizing network lifetime: ERBS-REE for resilient object detection and tracking in resource-constrained WSN environments", "*SIViP"*, Vol. 18, PP: 5189–5201, ISSN: 1179-2627.

[20]. Boothalingam, R. (2018), "Optimization using lion algorithm: a biological inspiration from lion's social behavior", "*Evolutionary Intelligence"*, Vol. 11, Issue 1, PP: 31–52, ISSN: 1864-5909.

[21]. Mareli, M., and Twala, B. (2017), "An adaptive Cuckoo search algorithm for optimization", "*Applied Computing and Informatics"*, Vol. 13, Issue 1, PP: 49-58, ISSN: 2210-8327.

[22]. Wang, G.-G., Deb, S., and Coelho, L. d. S. (2015), "Elephant Herding Optimization", "*2015 3rd International Symposium on Computational and Business Intelligence (ISCBI)"*, PP: 1-5, ISBN: 978-1-4673-7630-3.

[23]. Pedersen, M. E. H., & Chipperfield, A. J. (2010), "Simplifying Particle Swarm Optimization", "*Applied Soft Computing"*, Vol. 10, Issue 2, PP: 618-628, ISSN: 1568-4946.

[24]. Mirjalili, S., Gandomi, A. H., Mirjalili, S. Z., Saremi, S., Faris, H., & Mirjalili, S. M. (2017), "Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems", "*Advances in Engineering Software"*, Vol. 114, PP: 163-191, ISSN: 0965-9978